EEMS0016

U.S. DEPARTMENT OF ENERGY
SMARTMOBILITY
Systems and Modeling for Accelerated Research in Transportation

Energy Efficient Connected and Automated Vehicles

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Project Overview

Timeline	Barriers
• Project start date : Oct. 2016 • Project end date : Sep. 2019 • Percent complete : 10%	• Research on Connected & Automated Vehicles (CAVs) focused on safety • Little research combining CAVs and advanced powertrain technologies • Complexity of optimization • Lack of practical tools for energy-efficient CAV control development
Budget	**Partners**
• FY17-FY19 Funding: $2,480,000 • FY17 Funding Received : $836,000	• Argonne: lead • LLNL, NREL: provide data from real-world testing • Active discussions with universities (data) and OEMs (modeling needs)

Project Relevance

- Besides **electrification**, two major disruptive trends in the automotive world:
  Connectivity to the cloud, to other vehicles, to the infrastructure
  ⇒ *Information about surrounding environment, forecast of future driving*
  Automation, partial or full, enabled by sensor and machine vision
  ⇒ *Intelligent control of the velocity*
- Most research is focused on safety; little exploration of **energy** saving potential

Objectives: Perform control-focused research using simulation

⇒ ***Powertrain and velocity control strategies for minimum energy consumption and acceptable travel time***

⇒ ***Energy impacts for a broad range of powertrain technologies***

- Extends previous VTO-funded work on vehicle control and energy management of electrified vehicles
- Critical to the VTO mission:
  - Potential of **reducing vehicle energy consumption** through control
  - Will assess how expected energy efficiency gains from future vehicle **powertrain technologies** will change with **connectivity and automation**

Approach

- **Vehicle-centric**
  - Work is focused on a small number of vehicles, from single veh. to a platoon
  - Large system-wide aspects are not considered at this stage, but in future years, outputs of this project will be transferred to "system-wide" tools (e.g. traffic flow microsimulation, POLARIS, etc.)
- **Simultaneous control of velocity and powertrain**
  - Compare sequential control (1^{st} velocity, 2^{nd} powertrain) and combined control
  - Research how "optimal" velocity profiles differ for various powertrains
- **High-fidelity powertrain models**
  - Use Autonomie powertrain models : leverage large library of existing models of current and future technologies
  - Take into account drivability and dynamic aspects (e.g. engine starts, jerk, etc.)
- **Model-Based System Engineering (MBSE)**
  - Build upon Autonomie's MBSE framework
  - Use automated building, modularity, elementary building blocks, metadata, etc. to efficiently build scenarios for simulation

Approach

- Within SMART CAV pillar, this project helps quantify energy benefits from CAV operations, and will provide outputs to system-level tasks (e.g. microsimulation, city-wide models)
- Structure in 3 complementary focus areas:

Framework development

- Simulate driving on actual roads, with naturalistic drivers interacting with the road infrastructure and with other vehicles
- Simulink-based, integrated with Autonomie
- Will allow to simulate various control strategies on a broad range of scenarios and powertrains

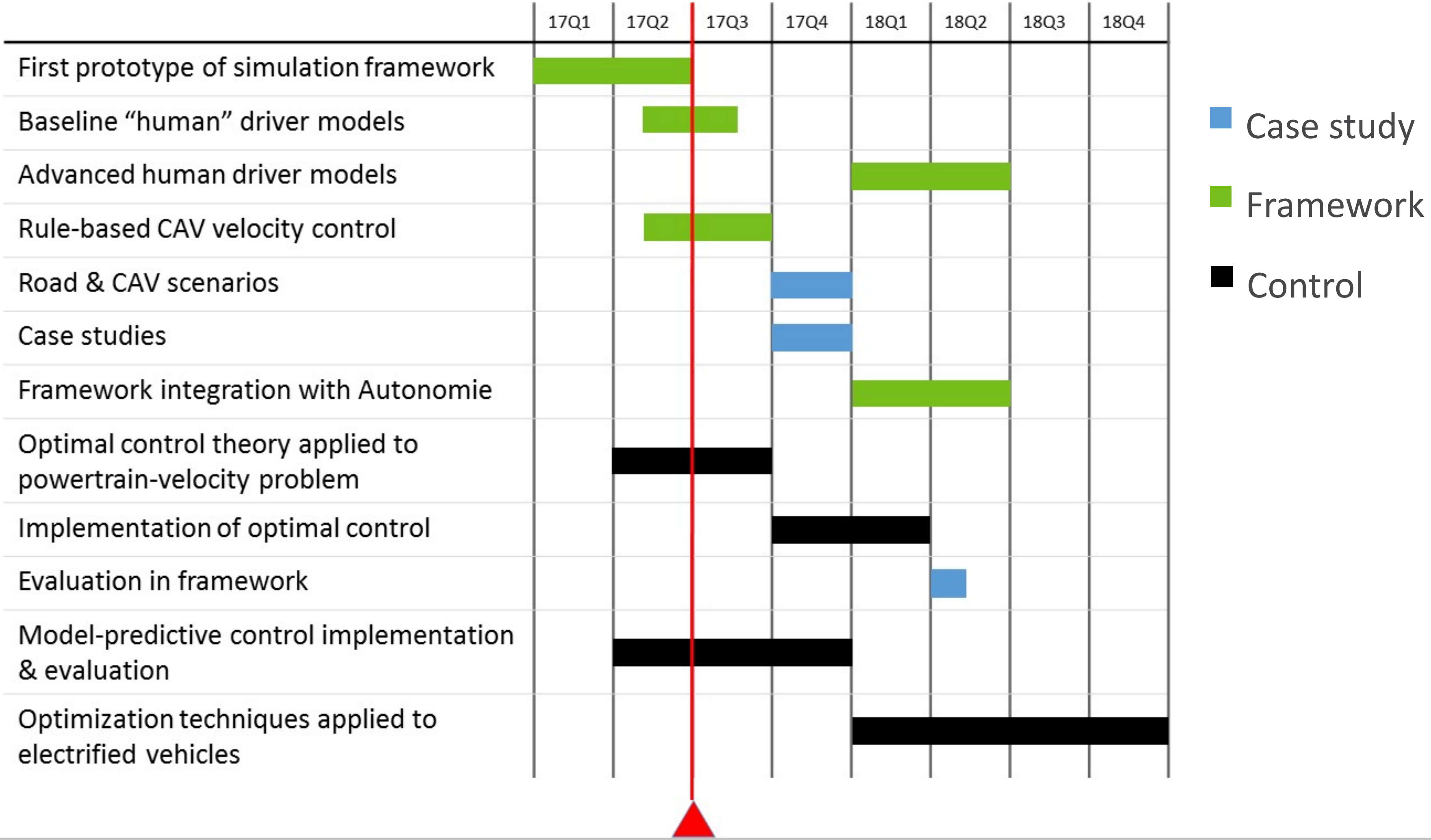
Control development

- Implement heuristic velocity control strategies from literature
- Research optimal control strategies, and develop implementations: Pontryagin Minimum Principle, Model-Predictive Control

Case studies and analysis

- Develop a broad range of road/connectivity/automation scenarios
- Quantify energy saving potential for various powertrains: conventional ICE, start-stop, hybrids, EVs, etc.

Milestones

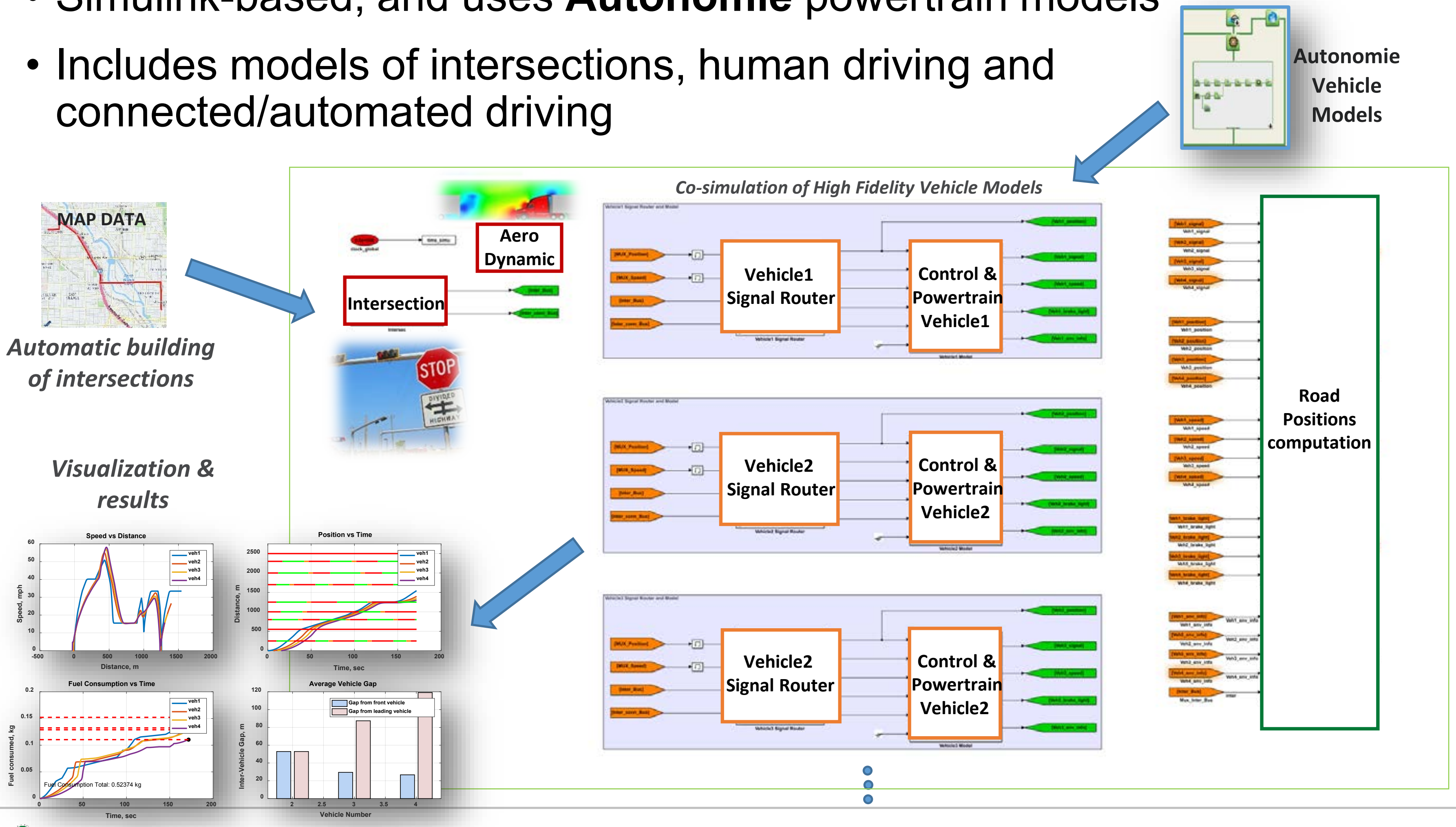


17Q1
17Q2
17Q3
17Q4
18Q1
18Q2
18Q3
18Q4
First prototype of simulation framework
Baseline "human" driver models
Advanced human driver models
Rule-based CAV velocity control
Road & CAV scenarios
Case studies
Framework integration with Autonomie
Optimal control theory applied to powertrain-velocity problem
Implementation of optimal control
Evaluation in framework
Model-predictive control implementation & evaluation
Optimization techniques applied to electrified vehicles
Case study
Framework
Control

TECHNICAL ACCOMPLISHMENTS

Framework for Integrated Powertrain-CAV Simulation

- Simulink-based, and uses **Autonomie** powertrain models
- Includes models of intersections, human driving and connected/automated driving

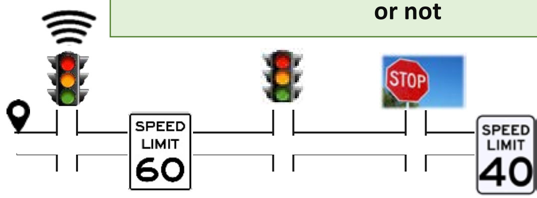


Framework Relies on Automated Building

Automated building of route model

Route definition in mapping tool (HERE)

Extraction of intersection types and speed limits; user chooses whether traffic lights are connected or not

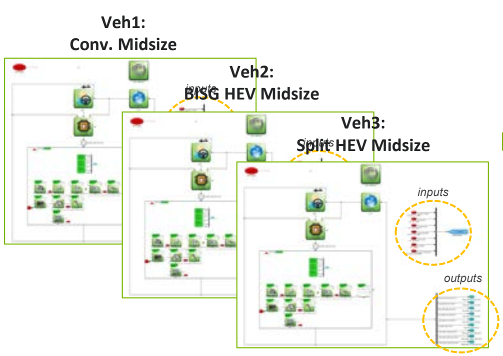


- **One intersection = one instance of corresponding intersection model**
- **Each intersection sends out state signals**

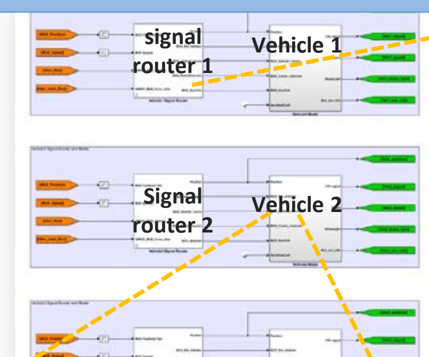
Speed limits = f(distance)

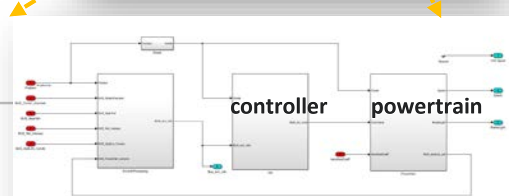
Automated building of vehicle and signal routers

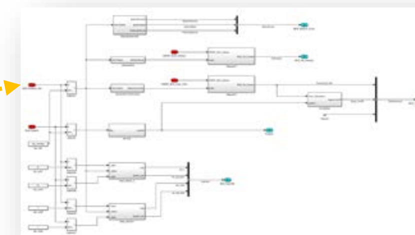
Definition/Selection of Vehicles in Autonomie



Building of signal router, vehicle, controller and powertrain blocks







*For each vehicle the **signal router** links the vehicle with relevant I/Os, to model real-world interactions:*

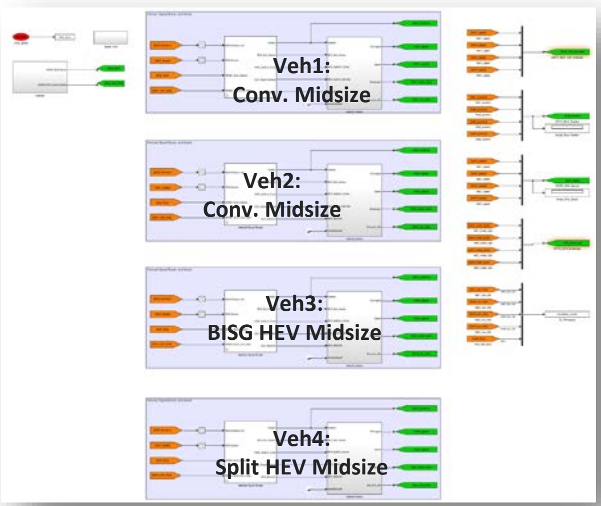
- *Vehicles ←→ vehicles (V2V Radio, sensors)*
- *Infrastructure → vehicles (V2I radio, image recognition – e.g. signal state)*
- *Infrastructure → driver ("visual" interpretation of road signage)*
- *Vehicles → driver (gap with preceding vehicle)*
- *Digital map → Vehicle (electronic horizon)*

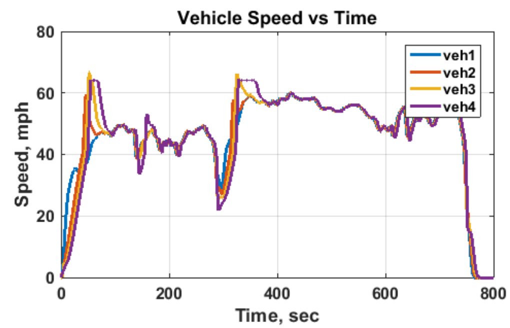
Multiple Scenarios Modeled

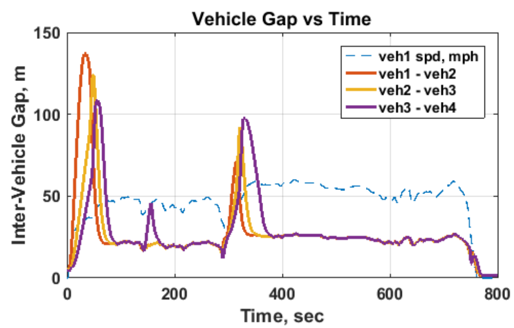
- Two main situations for both human and automated driving:
  - "**road-following**": target cruising speed at or below speed limit, stop at red light and stop sign, slow down at turns
  - "**car-following**": maintaining a safe distance with preceding vehicle
- **Human driving model**:
  - **Deterministic**: road-following and car-following with typical human reaction times, acceleration and deceleration profiles
  - **Probabilistic**: adding a probabilistic/stochastic aspect (future work)
- **Automated, non-connected driving model:**
  - Baseline similar to deterministic human model, but with different calibration (reaction time limited by sensor response time, reduced aggressivity)
  - Some potential for optimization for cruising, acceleration, approach, etc.
  - A model for: e.g. **Adaptive Cruise Control** (ACC)
- **Automated and connected driving model:**
  - Better knowledge about surrounding vehicles and road features ahead provides opportunity for optimization (e.g. traffic signal eco-approach)
  - A model for: **Cooperative ACC** (CACC), which results in shorter gap with preceding vehicle
- **Traffic conditions:**
  - Traffic not modeled intrinsically, due to limited number of simulated vehicles
  - Can be modeled with hybrid model of lead vehicle: "speed-trace-following" and "road-following"
  - Speed trace can be generated using constrained Markov chain algorithm

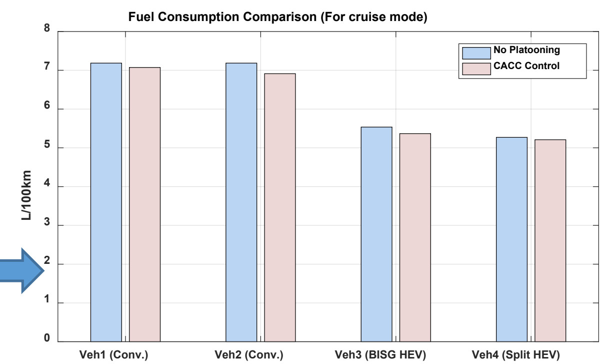
Use Case Example: Highway CACC with Various Powertrains

- Multi-vehicle run with a mix of powertrain technologies
- Lead vehicle follow EPA Highway drive cycle
- Following vehicles are “human-driven” at low-speeds, and switch to CACC above 40 mph
- Each vehicle aerodynamic drag is reduced as a function of gap (and speed?)



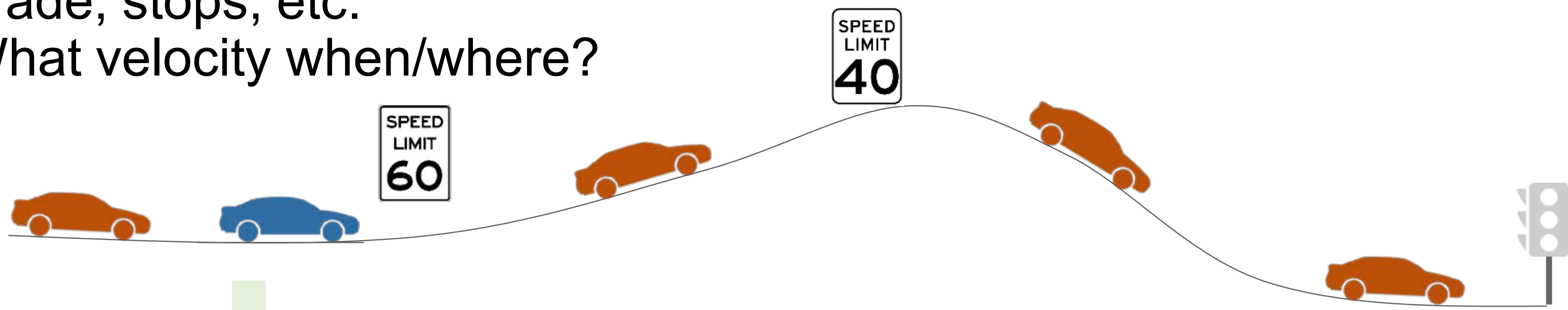




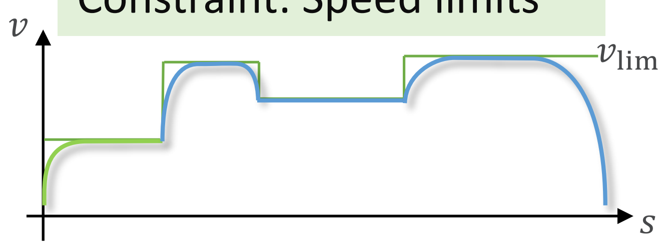


Identifying Optimal Velocity Control Using Optimal Control Theory

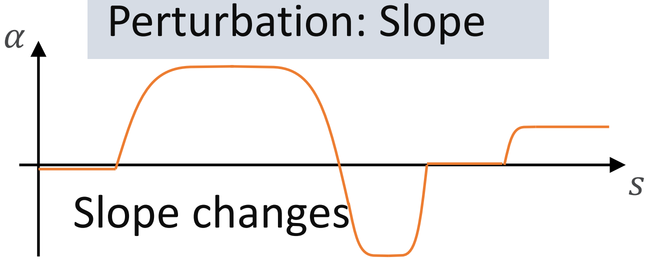
- Ego CAV is provided with various look-ahead information: speed limit, grade, stops, etc.
- What velocity when/where?



Constraint: Speed limits

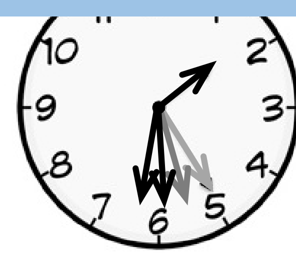


Perturbation: Slope



Slope changes

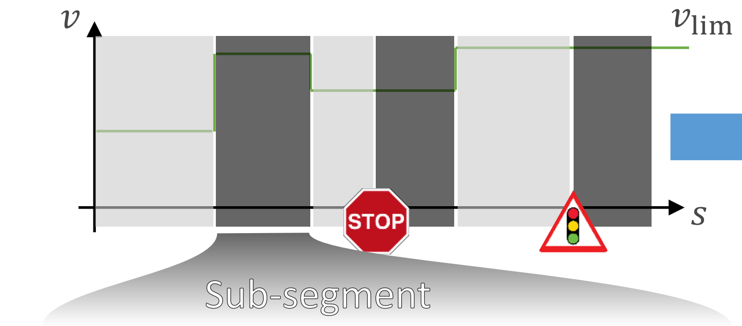
Final condition: terminal time

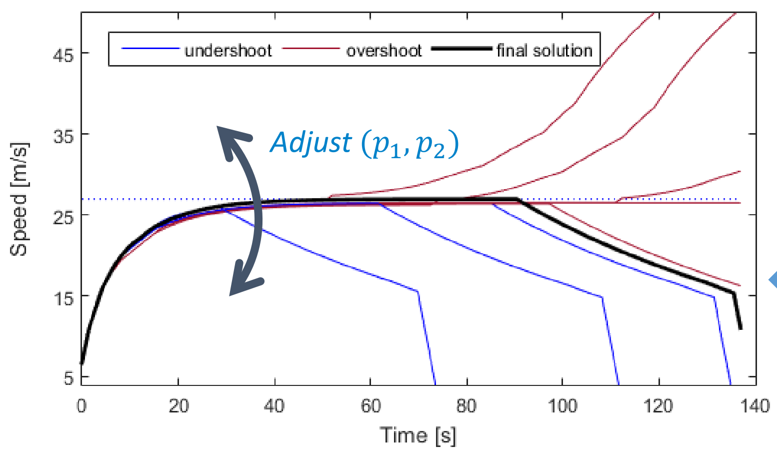


CAV optimization problem is often an energy consumption vs. travel trade-off

Applying the Pontryagin's Minimum Principle (PMP) to Compute Engine Torque in a Conventional Vehicle

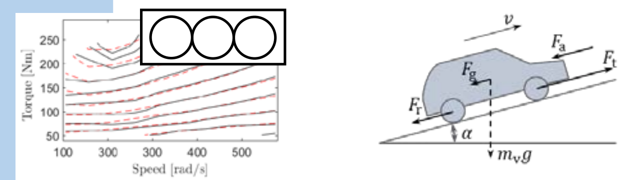
Divide future in uniform driving conditions (speed limit, slope, etc.)





Varying the ***parameter pair*** *results in different trajectories: so-called* Single Shooting Method

Control Oriented Models



powertrain components + long. veh. dynamics

Math. Formulation of OCP

$$\min \quad J = \int_0^{t_f} \dot{m}_f(v, T_{eng})\, dt$$

$$\text{s.t.} \quad \dot{v} = f(v, T_{eng})$$

Hamiltonian: $H = \dot{m}_f + \lambda\, \dot{v}$

Derive using PMP conditions

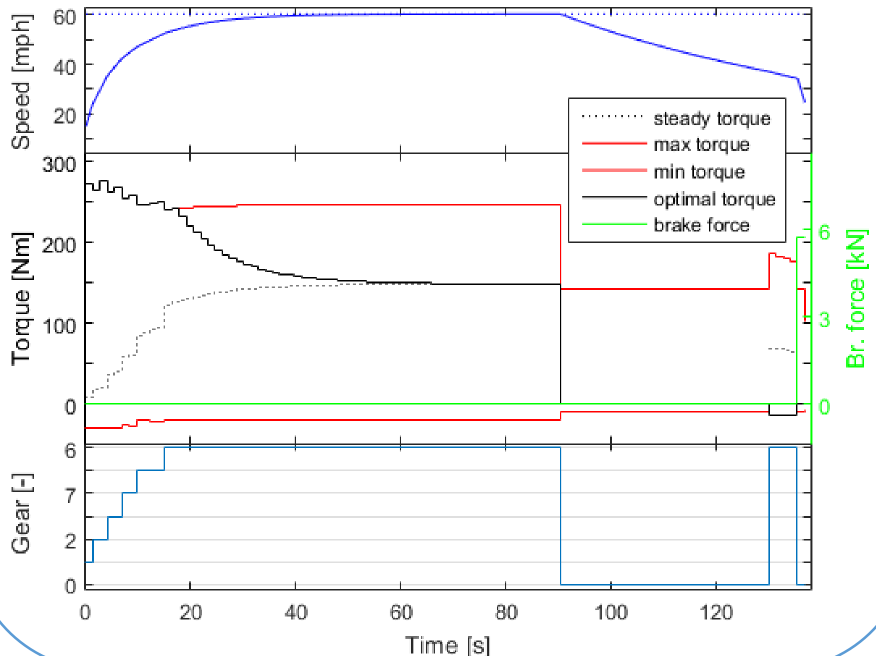
Optimization Algorithm

$$T^*_{eng}(t) = \psi(v(t), p_1, p_2), t \in [t_0, t_f]$$

Calculates the driving ***torque, gear, brake*** *(optimized control) depending on* ***two parameters*** *that are adjusted upon the constraints*

PMP Results

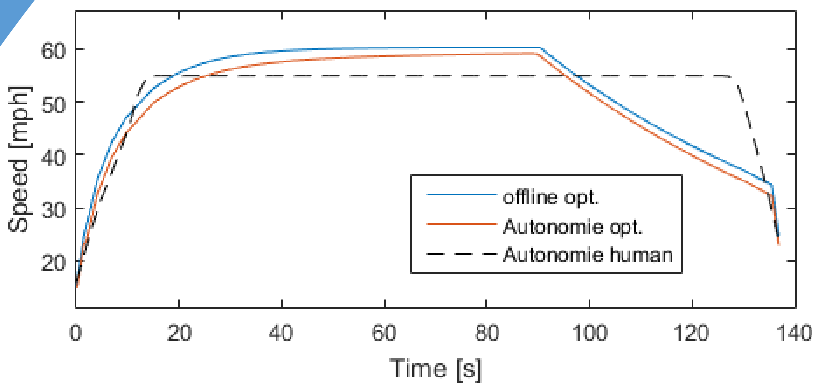
Offline optimization



open-loop control

AUTONOMIE

Simulation result



Speed deviation (—offline vs. —Autonomie) is mainly due to time delay in gear shifting and lack of feedback loop

Scenario:

Start speed =15 mph; end speed = 25 mph

Target distance 1.98 Mile.

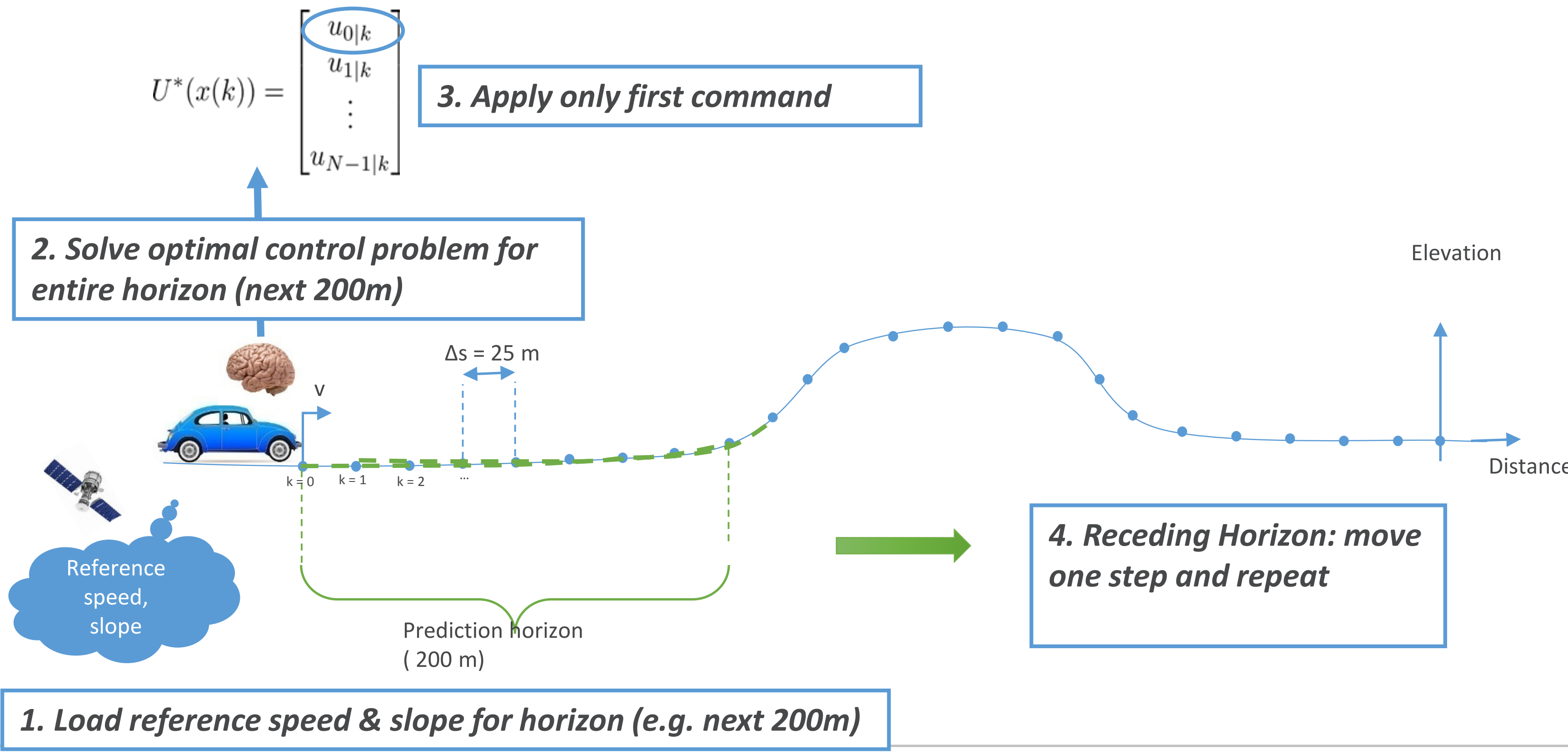
Human driver completed in 136.9 s.

Opt. algorithm aims at the same time.

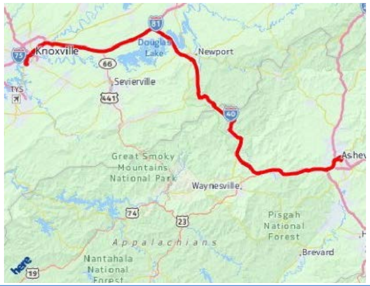
	Fuel [gallon]	Distance [mile]	Fuel Economy [mpg]
Opt.	0.0589	1.927	32.7
Human	0.0712	2.003	28.2

Implementation-Oriented Control: Model-Predictive Control (MPC)

- MPC is a framework for taking into account continuous look-ahead information for making optimal control decision, while including a feedback-loop (receding horizon)
- Very efficient when model is linear or quadratic ($\Rightarrow$ developed quadratic models for conventional vehicle)
- Scenario: highway cruise-control $\Rightarrow$ what optimal torque/velocity?



Application of MPC to a Conventional Vehicle

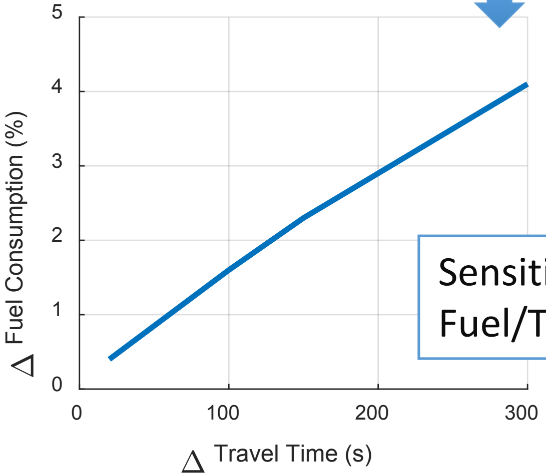


Route definition: Knoxville to Asheville (highway with grades)

Extraction of route attributes (slope, speed limits) from HERE maps

Offline MPC optimization with backward model

Simulation in Autonomie: "optimal" vs. reference speed trace



Sensitivity analysis: Fuel/Time trade-off

Preliminary results show up to 4% fuel savings compared to reference case (cruise control at set below speed limit)
But it comes at the expense of longer travel time (+5 min over 2h trip)

Response to Previous Year Reviewers' Comments

Project was not reviewed in the past

Partnerships and Collaborations

Lawrence Livermore National Laboratory	LLNL provides aerodynamic drag reduction coefficients from 3D modeling and wind tunnel
NREL NATIONAL RENEWABLE ENERGY LABORATORY	NREL tests platooning trucks and provides results and data from real-world testing
TU/e Technische Universiteit Eindhoven University of Technology	Collaboration on designing MPC control
AUBURN UNIVERSITY	Exchanges about control for platooning trucks (Auburn tests them on their test track)
VirginiaTech Transportation Institute	Active discussion about real-world driving data (human and connected/automated)
U.S. Department of Transportation Federal Highway Administration Turner-Fairbanks Highway Research Center	Active discussion about Autonomie-based framework for CAV simulation
here	Digital maps with detailed road features

Remaining Challenges and Barriers

- **Complexity** of control problem
  - Up to 3 control variables (e.g. parallel HEV: engine & motor torques, gear), 3 states (velocity, position/time, battery SOC) + drivability constraints (e.g. limited engine starts)
  - Large number of scenarios sometime require different problem formulations
  - Implementation of theoretical concepts requires taking into account transients and corner cases
- **Calibration**: optimal control often requires calibration to find the right trade-off between various objectives: energy, travel time, drivability
- **Modeling human driving**: human behavior is not fully deterministic, and depends on individuals (e.g. aggressive vs passive drivers)

Proposed Future Research

- **Simulation framework for CAV**:
  – Continue development in FY18, with a focus on better integration with Autonomie
  – Improve driver model to add stochasticity (FY18):
    – Tap into driver models in traffic flow micro-simulators
    – Use real-world datasets (e.g. NGSIM, SHRP2)
  – Develop processes to link to traffic flow microsimulators
- **Case studies** (FY17):
  – Implement **rule-based** “eco-driving” algorithms inspired from literature for connected automated driving
  – Run case study for connected traffic signal intersection **eco-approach** for various powertrains
  – Use aero data from LLNL to run study on **truck platooning** and compare with real-world test data from NREL ($\Rightarrow$ towards validation)
- **Optimal control**
  – FY17: work toward implementation of optimal control (MPC, PMP) for conventional vehicles
  – FY18: explore optimal control for EVs and HEVs
  – Develop “optimization-based” heuristic control in case optimal control proves to be too complex

Any proposed future work is subject to change based on funding levels

Summary

- This project supports DOE's **SMART** goal of estimating the impact of future mobility systems, as well as proposing solutions to make them more energy-efficient.
- We study how **connectivity/automation** (e.g. platooning, eco-approach, "self-driving) and **advanced powertrain technologies** (HEVs, EVs, etc.) interact $\Rightarrow$ *synergies or diminishing returns?*
- **Advanced control of velocity and powertrain** will be implemented in a framework with **realistic information flows**, in combination with **high-fidelity plant models** and for a wide **array of scenarios**

  $\Rightarrow$ *More **accurate** estimation CAV energy efficiency*

  $\Rightarrow$ *Energy-saving control algorithms closer to real-world **implementation***

  $\Rightarrow$ *Preliminary results show **energy saving potential***
- **Framework** for CAV simulation will eventually be **shared** with the research/industry community to foster further development and **deployment** of energy-saving CAV control algorithms.